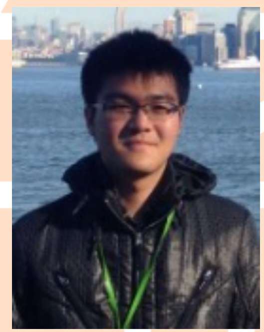
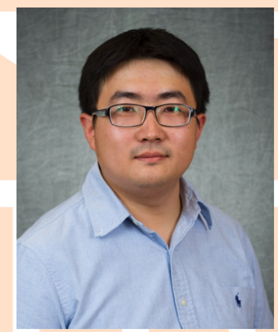
GUIDE: Group Equality Informed Individual Fairness in Graph Neural Networks



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[1]University of Virginia

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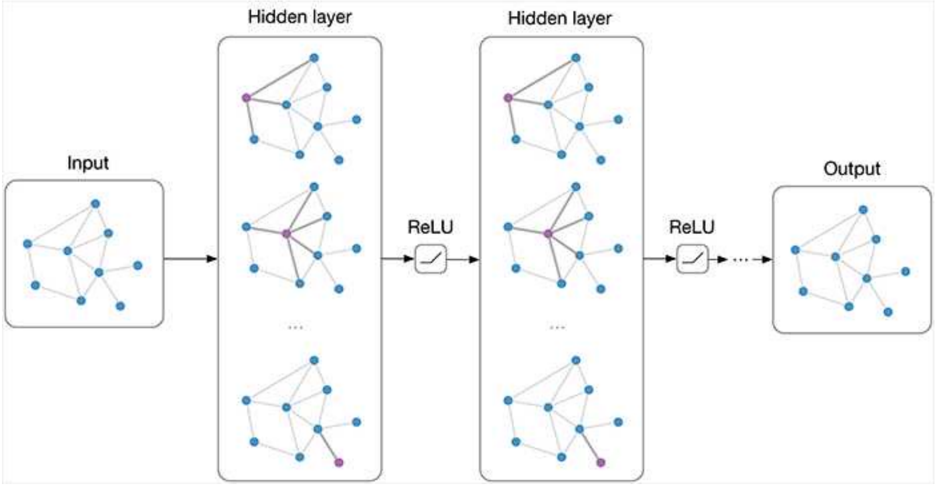
Background Introduction

Graph neural networks

- Leverage graph structure
- Direct learn representation for target task



- Applications: social network modeling, decision making

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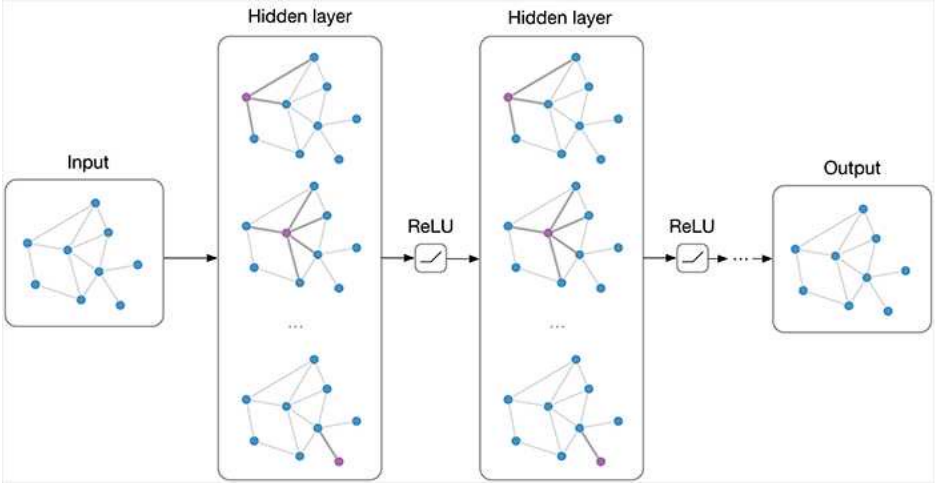

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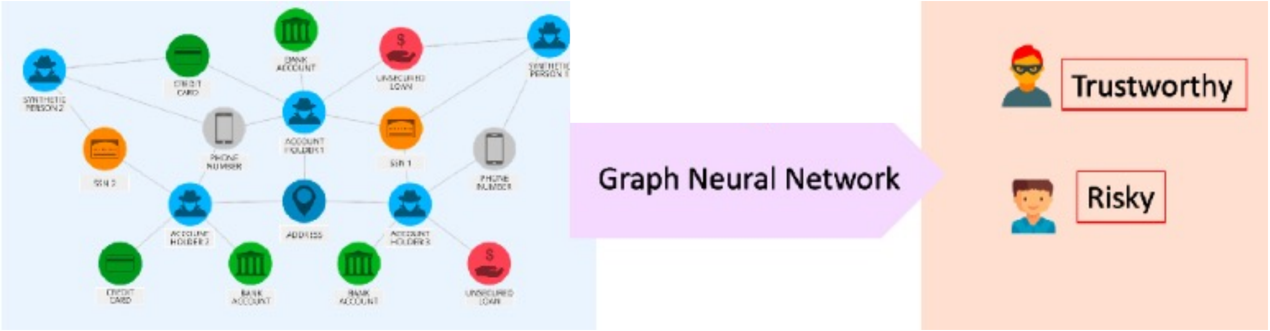

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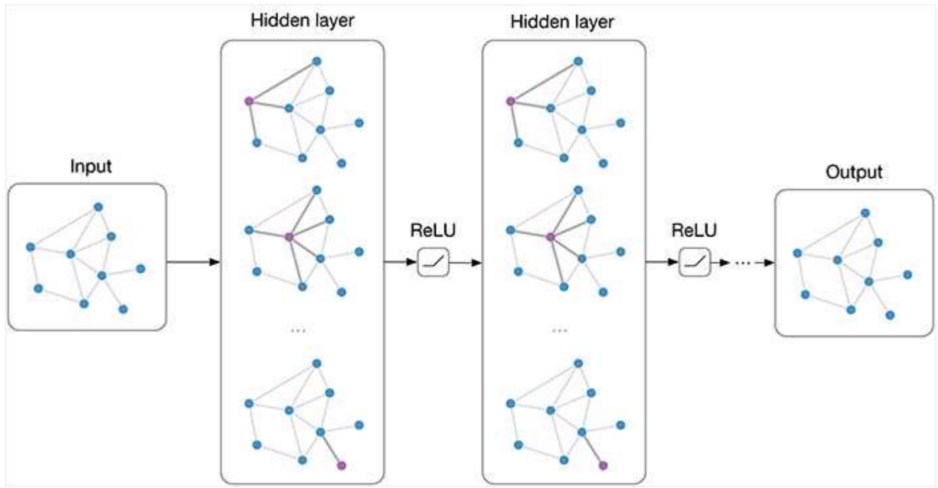

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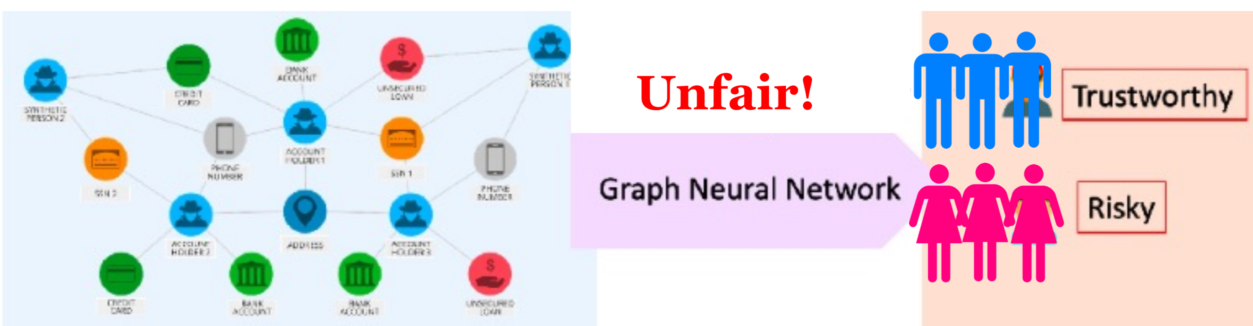


Background Introduction

Fairness

- Group fairness
- Individual fairness

Background Introduction

Fairness

- Group fairness
- Individual fairness

Group fairness

Different groups defined by protected attributes receive fair share of interests

Individual fairness

Similar individuals receive similar treatments or outcomes

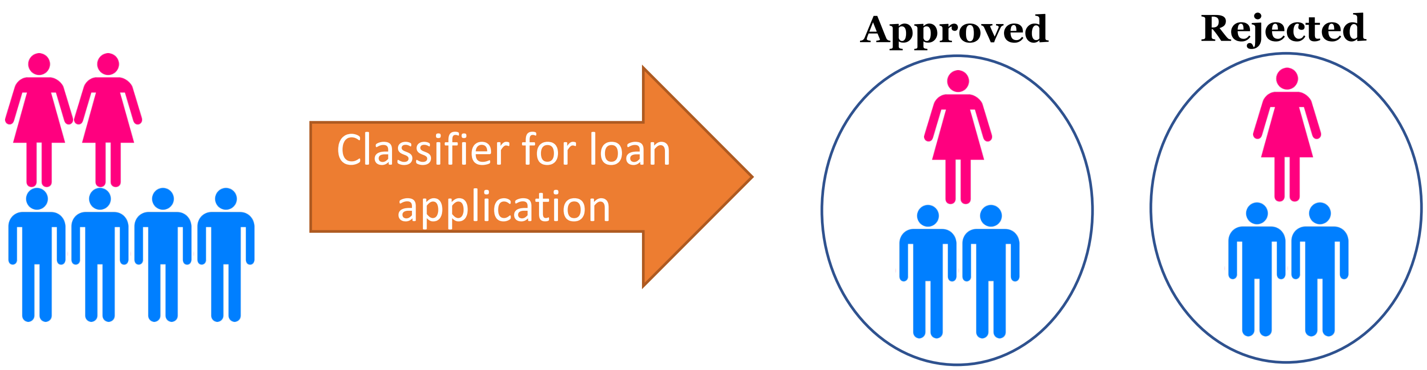
Background Introduction

Group Fairness: Statistical Parity

- People from **different groups defined by protected attributes** have equal probability of receiving certain outcomes

$$P(\hat{Y} \mid A = 0) = P(\hat{Y} \mid A = 1)$$

- Example:



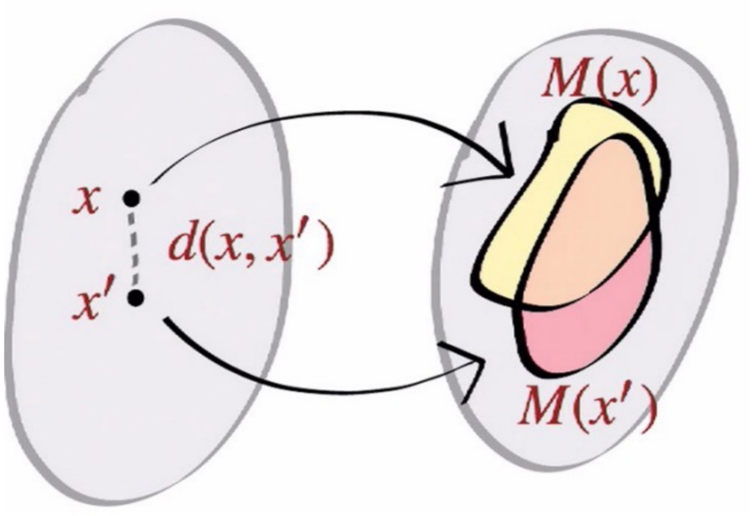
Background Introduction

Individual Fairness

- Giving **similar individuals** similar outcomes
- Formulation [1, 2, 5]

Lipschitz Condition

$$d_1\big(M(x), M(y)\big) \le L d_2(x, y), \forall x, y \in \boldsymbol{\mathcal{V}}$$
$$L > 0$$



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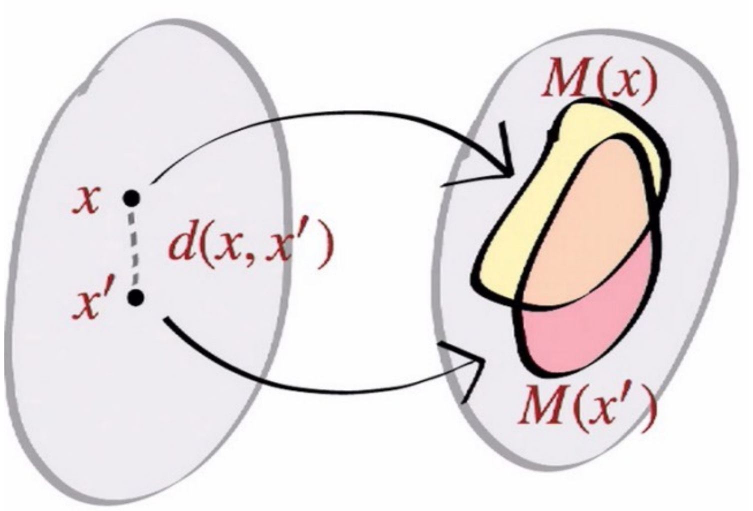
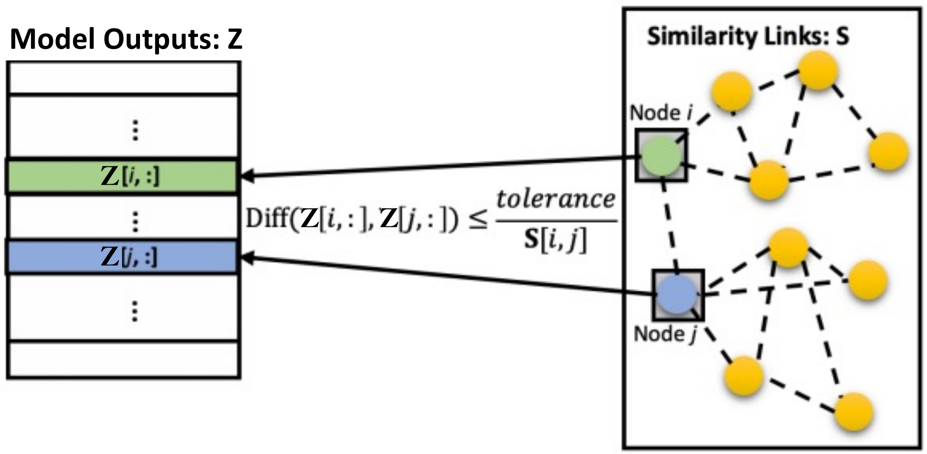


Existing works [2, 5]

$$\sum_{v_i \in \mathcal{V}} \sum_{v_j \in \mathcal{V}} \|\mathbf{Z}[i,:] - \mathbf{Z}[j,:]\|_2^2 \, \mathbf{S}[i,j]$$



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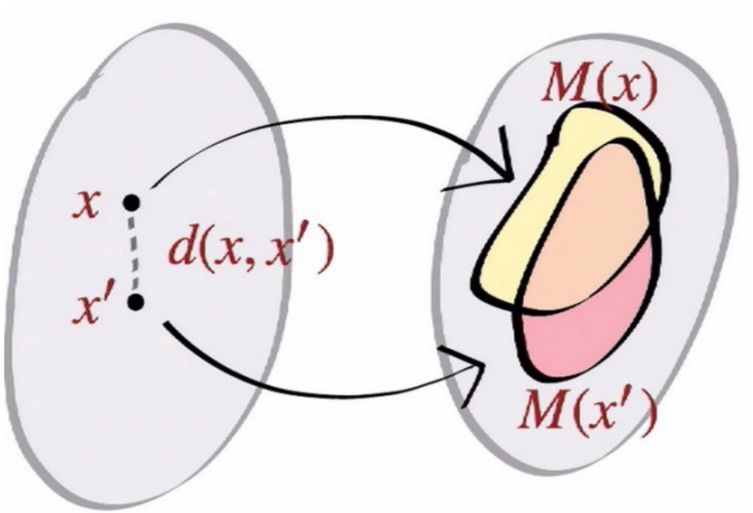

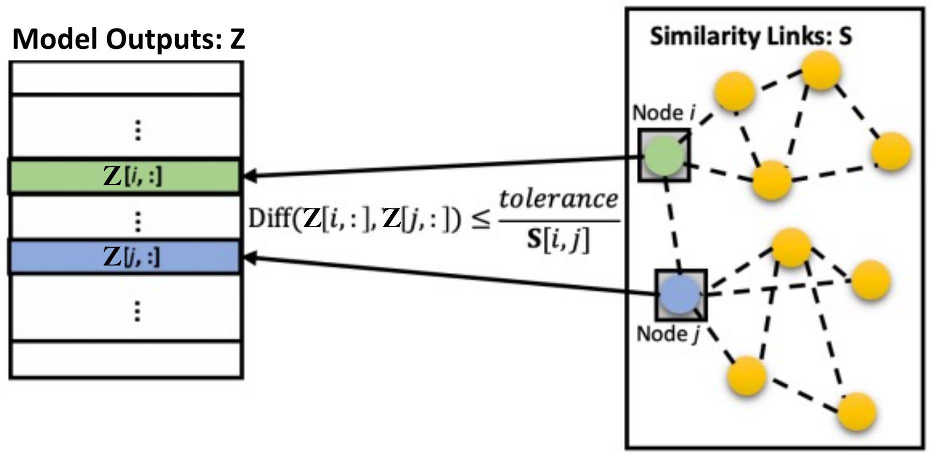

Background Introduction

Deeper understanding of existing work

- Existing works [2, 5] utilize the equation on the right to measure individual (un)fairness

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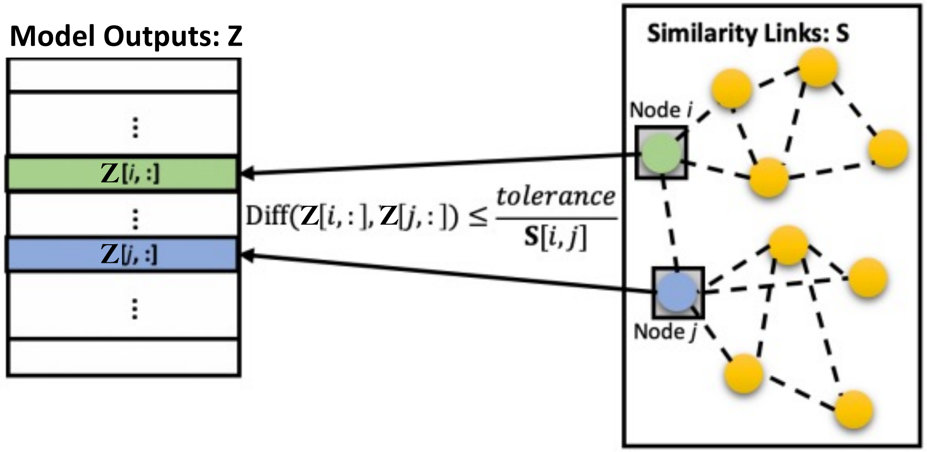

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- Existing works [2, 5] utilize the equation on the right to measure individual (un)fairness
- They minimize this sum to optimize individual fairness

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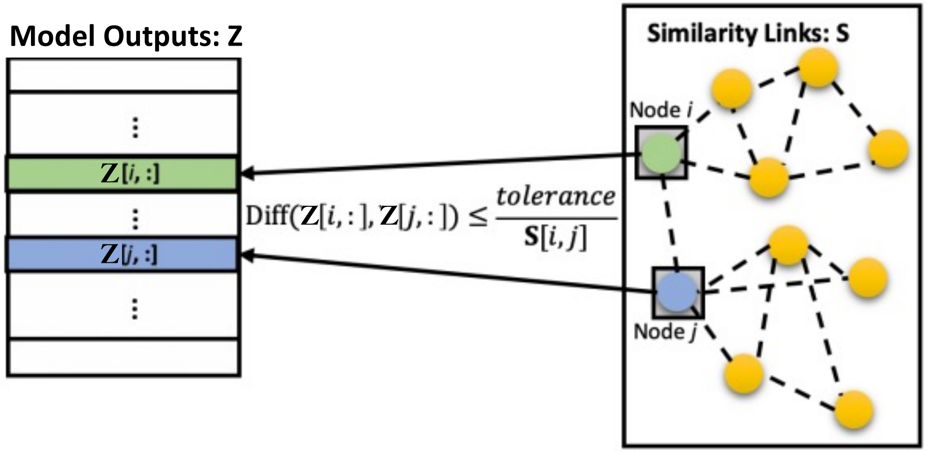

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Existing works [2, 5]

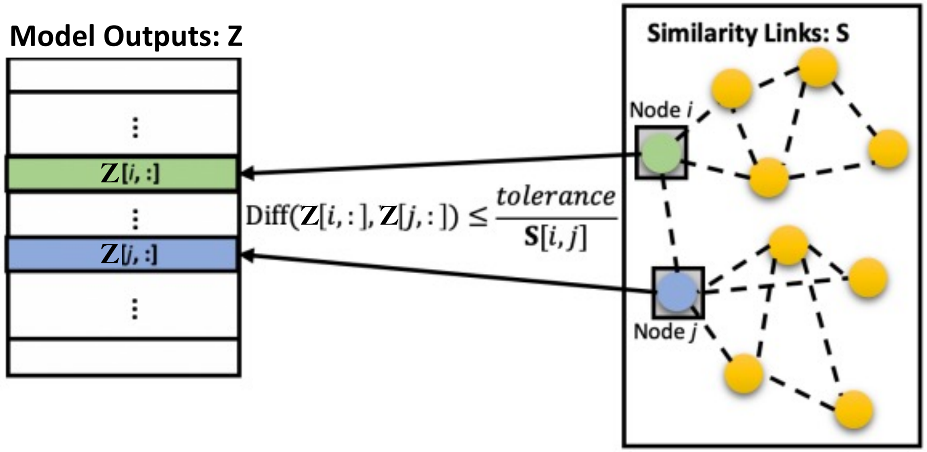
$$\sum_{v_i \in \mathcal{V}} \sum_{v_j \in \mathcal{V}} \|\mathbf{Z}[i,:] - \mathbf{Z}[j,:]\|_2^2 \, \mathbf{S}[i,j]$$

Why does it work?

- Constraining scalar for node pair v_i, v_j

$$\epsilon_{i,j} = \frac{d_1(M(v_i), M(v_j))}{d2(v_i, v_j)} = ||\mathbf{Z}[i,:] - \mathbf{Z}[j,:]||_2^2 \mathbf{S}[i,j]$$

smaller->fairer



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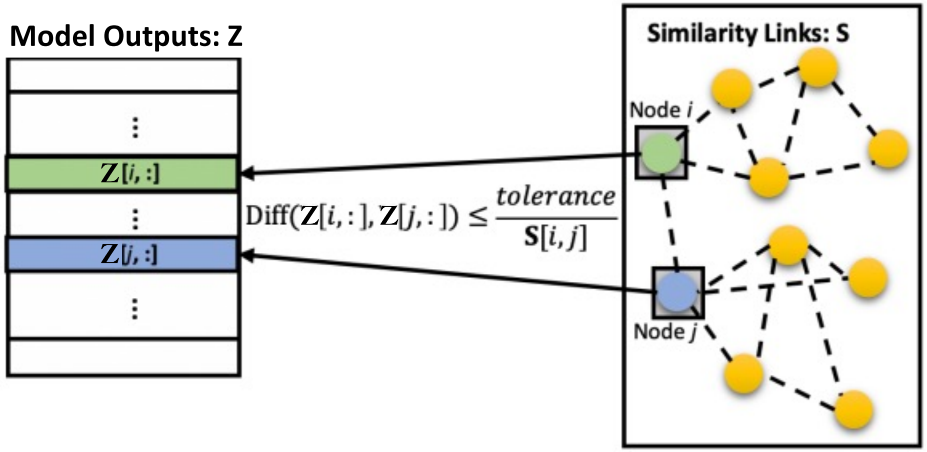
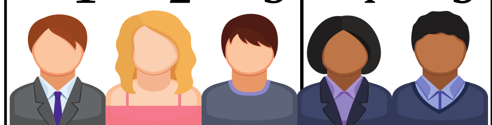


Equivalent to minimizing average constraining scalar **for the entire dataset**

Problem Motivation

Constraining scalars for a specific individual

A **specific individual** $\boldsymbol{v_i}$ has constraining scalars against all individuals in the dataset



	Group W			Group B	
	v_1	v_2	v_3	v_4	v_5
v_1	$\boldsymbol{\epsilon_{1,1}}$	$\boldsymbol{\epsilon_{1,2}}$	$\boldsymbol{\epsilon_{1,3}}$	$\boldsymbol{\epsilon_{1,4}}$	$\boldsymbol{\epsilon_{1,5}}$
v_2	$\boldsymbol{\epsilon_{2,1}}$	$\boldsymbol{\epsilon_{2,2}}$	$\boldsymbol{\epsilon_{2,3}}$	$\boldsymbol{\epsilon_{2,4}}$	$\boldsymbol{\epsilon_{2,5}}$
v_3	$\boldsymbol{\epsilon_{3,1}}$	$\boldsymbol{\epsilon_{3,2}}$	$\boldsymbol{\epsilon_{3,3}}$	$\boldsymbol{\epsilon_{3,4}}$	$\boldsymbol{\epsilon_{3,5}}$
v_4	$\boldsymbol{\epsilon_{4,1}}$	$\boldsymbol{\epsilon_{4,2}}$	$\boldsymbol{\epsilon_{4,3}}$	$\boldsymbol{\epsilon_{4,4}}$	$\boldsymbol{\epsilon_{4,5}}$
v_5	$\boldsymbol{\epsilon_{5,1}}$	$\boldsymbol{\epsilon_{5,2}}$	$\boldsymbol{\epsilon_{5,3}}$	$\boldsymbol{\epsilon_{5,4}}$	$\boldsymbol{\epsilon_{5,5}}$

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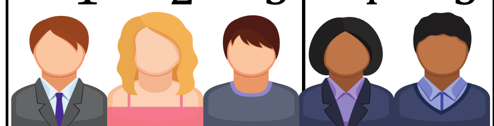

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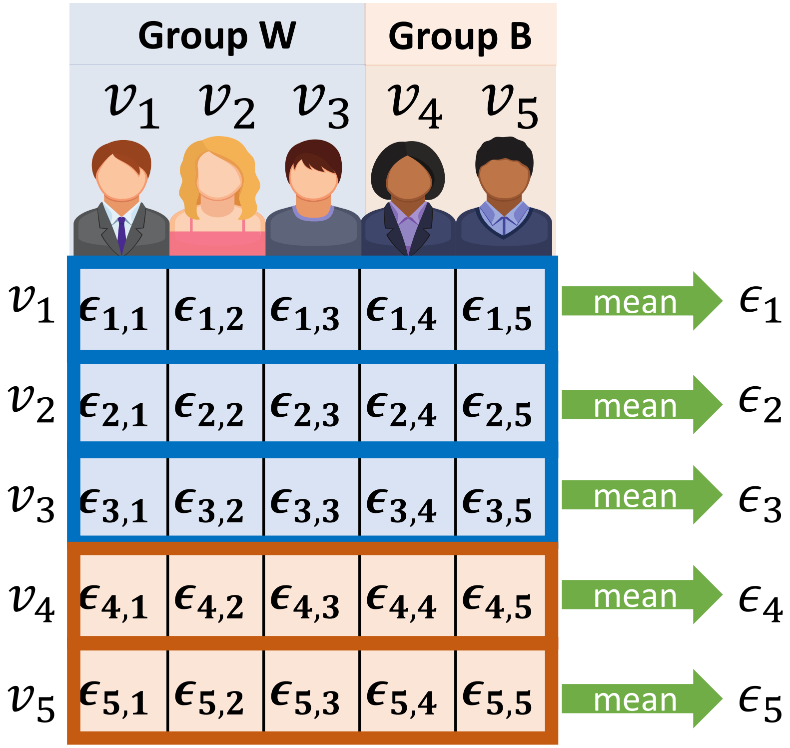
v_3	$\boldsymbol{\epsilon_{3,1}}$	$\boldsymbol{\epsilon_{3,2}}$	$\boldsymbol{\epsilon_{3,3}}$	$\boldsymbol{\epsilon_{3,4}}$	$\boldsymbol{\epsilon_{3,5}}$
v_4	$\boldsymbol{\epsilon_{4,1}}$	$\boldsymbol{\epsilon_{4,2}}$	$\boldsymbol{\epsilon_{4,3}}$	$\boldsymbol{\epsilon_{4,4}}$	$\boldsymbol{\epsilon_{4,5}}$
v_5	$\boldsymbol{\epsilon_{5,1}}$	$\boldsymbol{\epsilon_{5,2}}$	$\boldsymbol{\epsilon_{5,3}}$	$\boldsymbol{\epsilon_{5,4}}$	$\boldsymbol{\epsilon_{5,5}}$

$\xrightarrow{\text{mean}} \epsilon_1$

Problem Motivation

Constraining scalars for different groups

Members of a group also have constraining scalars and the average indicates **the level of individual fairness for this group**



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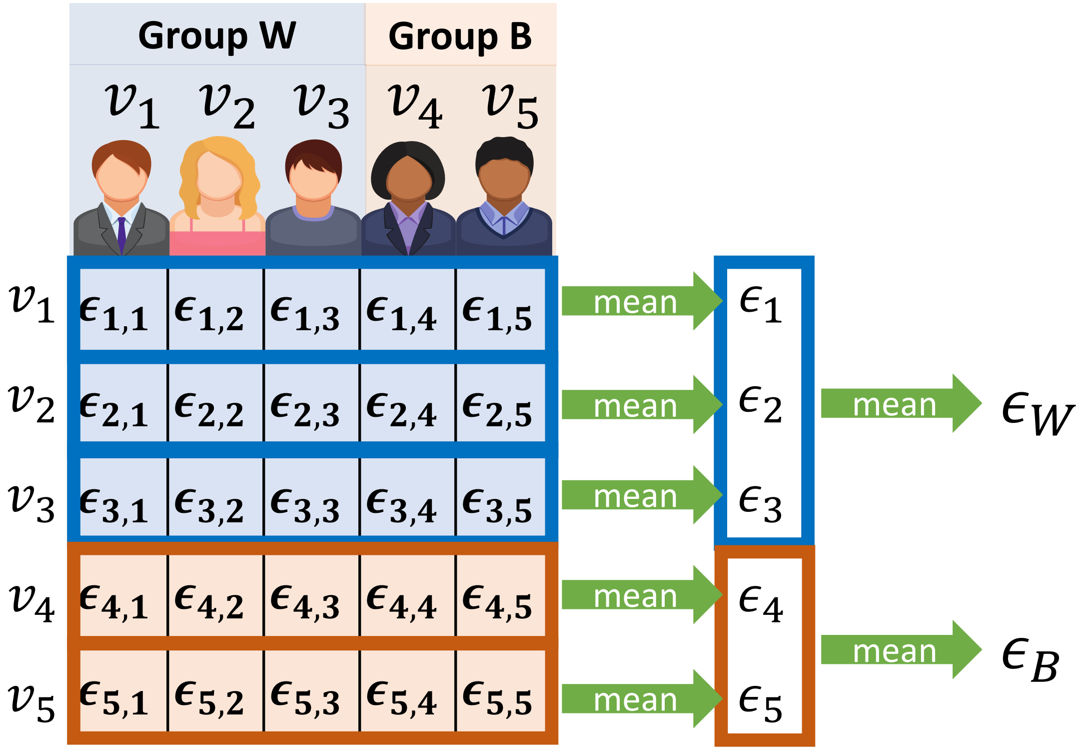

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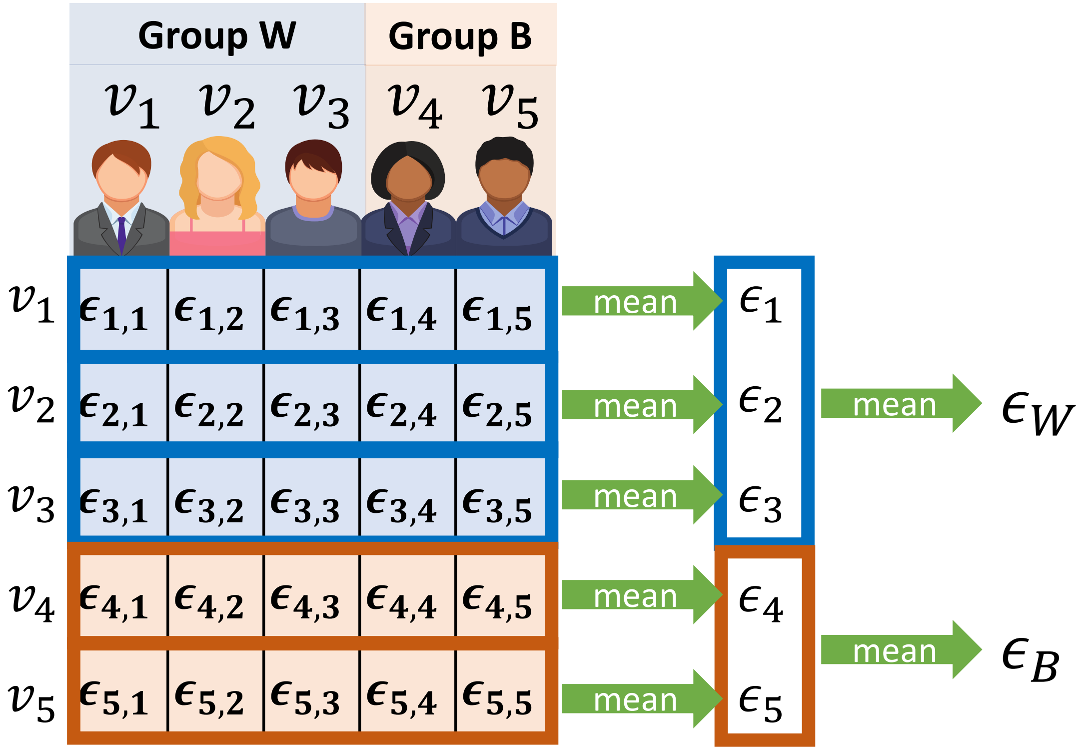
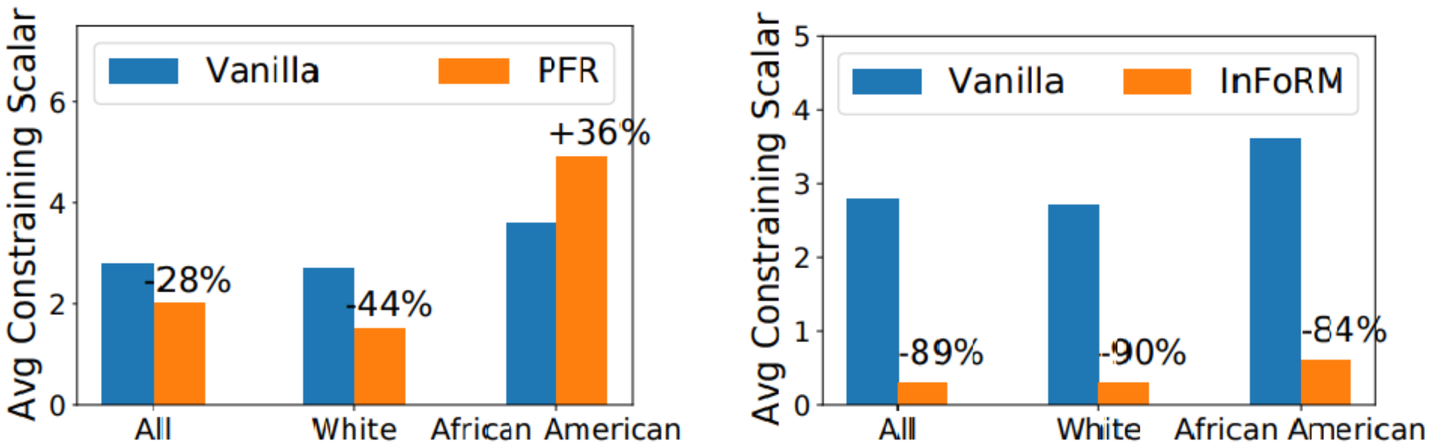


$$\epsilon_W \stackrel{?}{=} \epsilon_B$$

Problem Motivation

Existing works [2,5] actually lead to group inequalities of individual fairness



(a) GNN-PFR (b) GNN-InFoRM

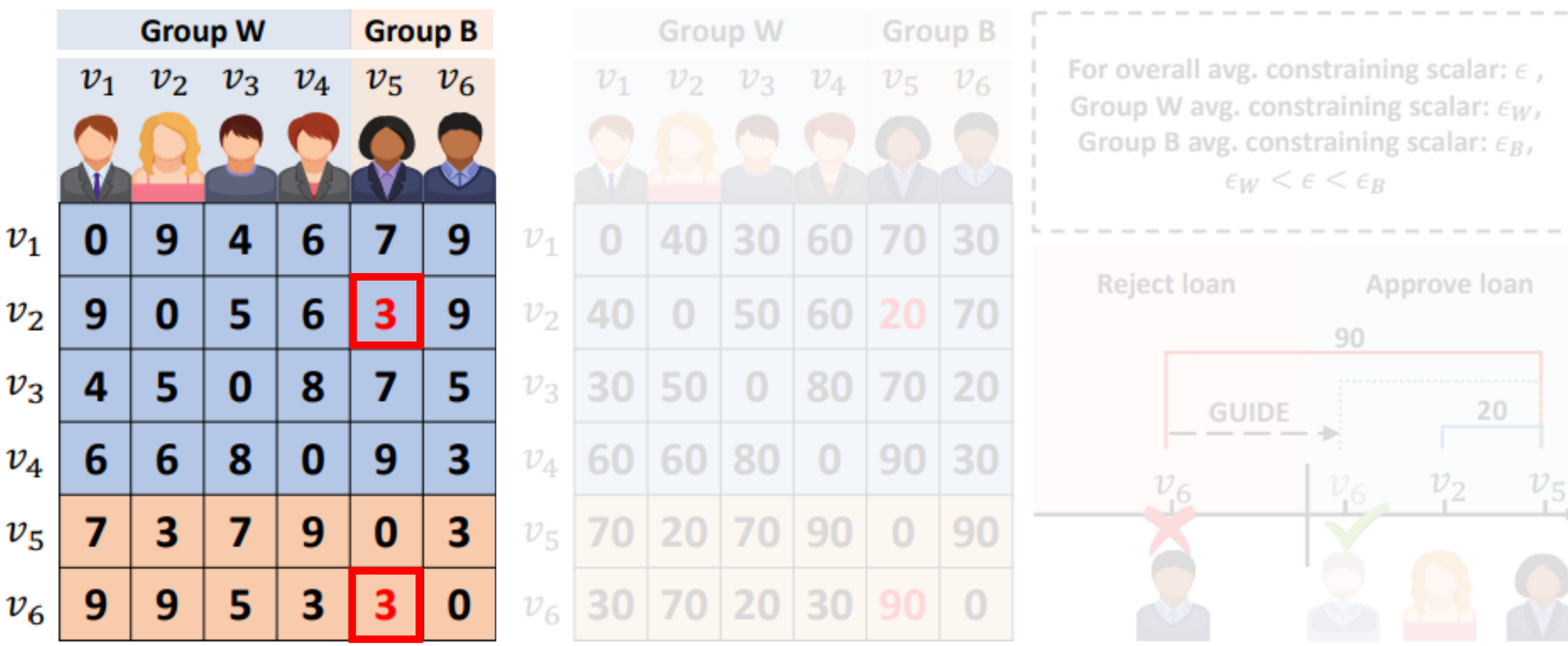
- **Disparate optimization** for different demographic groups
- **Privileged group** experiences better fairness optimization

PFR [2]
Preprocessing algorithm to produce individually fair embeddings
InFoRM [5]
Preprocessing/in-processing/post-processing algorithm to yield individually fair node embeddings

Problem Motivation

Why does the group equality of individual fairness matter?

Assume $\epsilon_W < \epsilon < \epsilon_B$



(a) Node input distance matrix from metric d_2

(b) Node output distance matrix from metric d_1

(c) Unfair consequences from group disparity of IF

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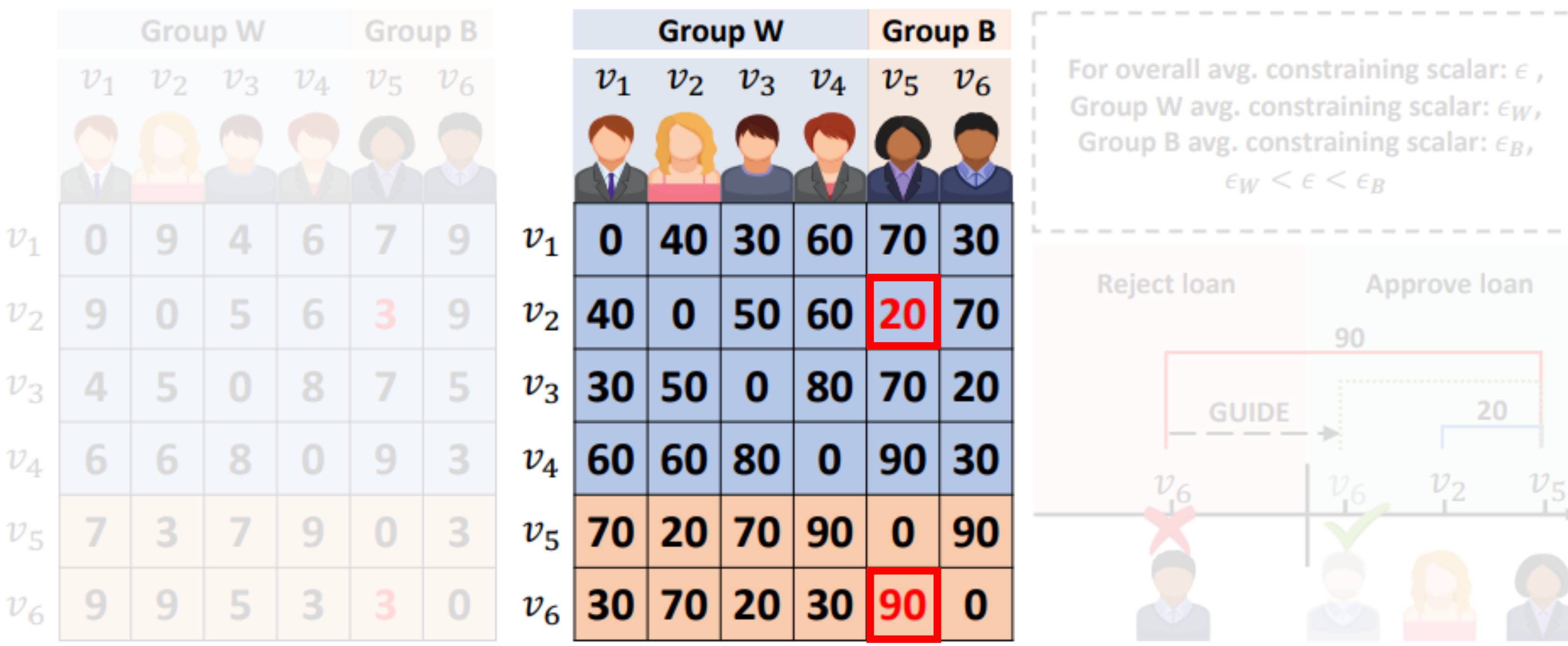

	v_1	v_2	v_3	v_4	v_5	v_6
v_1	0	9	4	6	7	9
v_2	9	0	5	6	3	9
v_3	4	5	0	8	7	5
v_4	6	6	8	0	9	3
v_5	7	3	7	9	0	3
v_6	9	9	5	3	3	0

(a) Node input distance matrix from metric d_2

	v_1	v_2	v_3	v_4	v_5	v_6
v_1	0	40	30	60	70	30
v_2	40	0	50	60	$\boxed{20}$	70
v_3	30	50	0	80	70	20
v_4	60	60	80	0	90	30
v_5	70	20	70	90	0	90
v_6	30	70	20	30	$\boxed{90}$	0

(b) Node output distance matrix from metric d_1

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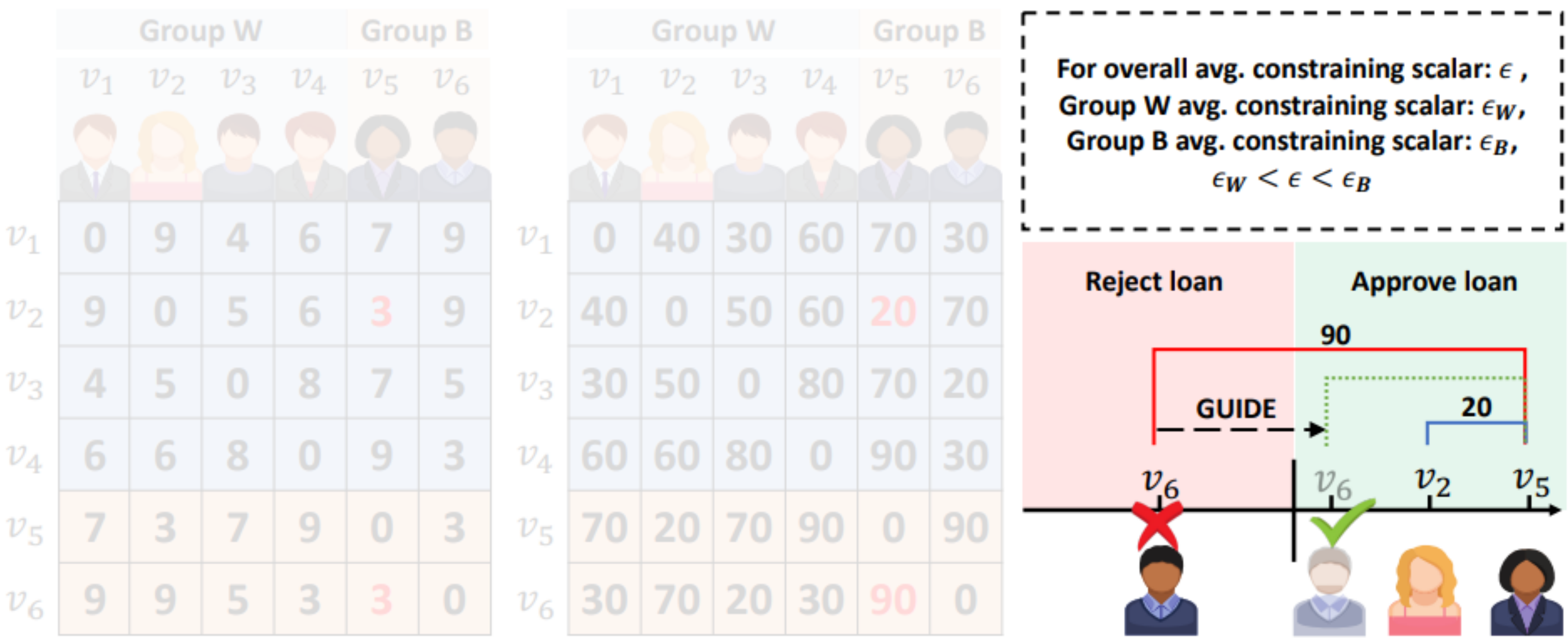


(a) Node input distance matrix from metric d_2

(b) Node output distance matrix from metric d_1

(c) Unfair consequences from group disparity of IF

Methodology

Metric for individual (un)fairness for a group

- Overall individual (un)fairness [2, 5]

$$\sum_{v_i \in \mathcal{V}} \sum_{v_j \in \mathcal{V}} \|\mathbf{Z}[i,:] - \mathbf{Z}[j,:]\|_2^2 \, \mathbf{S}[i,j]$$

- **Individual (un)fairness for a group**

Methodology

Metric for individual (un)fairness for a group

- Overall individual (un)fairness [2, 5]

$$\sum_{v_i \in \mathcal{V}} \sum_{v_j \in \mathcal{V}} \|\mathbf{Z}[i,:] - \mathbf{Z}[j,:]\|_2^2 \, \mathbf{S}[i,j]$$

- **Individual (un)fairness for a group $\mathcal{V}_p$**
  - Include both **intra-group and inter-group** evaluations for completeness

$$U_p = \frac{\sum_{v_i \in \mathcal{V}_p} \sum_{v_j \in \mathcal{V}} \|\mathbf{Z}[i,:] - \mathbf{Z}[j\ :]\|_2^2 \, \mathbf{S}[i,j]}{m_p}$$

Methodology

Metric for group disparity of individual fairness

- Propose a new metric:

  Group disparity of individual fairness (GDIF)

Methodology

Metric for group disparity of individual fairness

- Propose a new metric:

  Group disparity of individual fairness (GDIF)
- How to measure disparity for two groups $\mathcal{V}_p$ and $\mathcal{V}_q$?

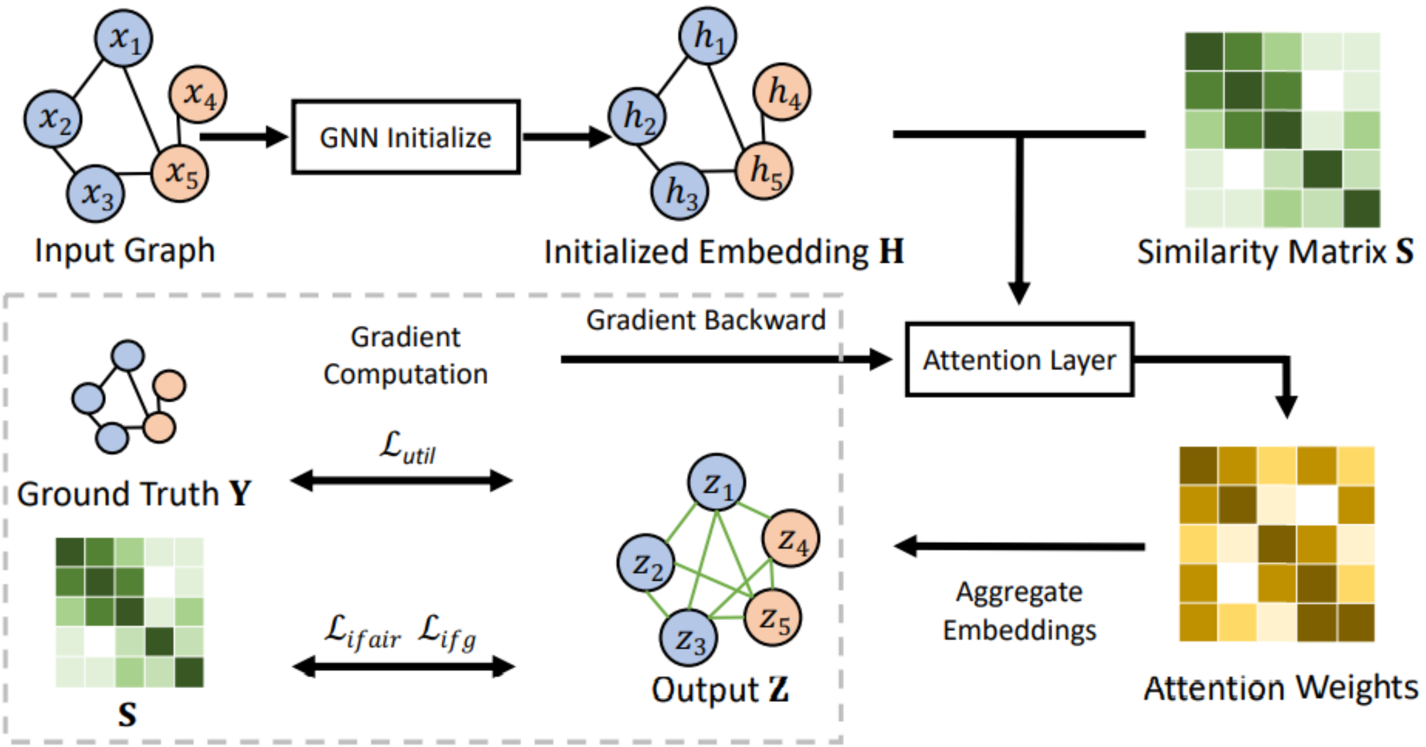
$$GDIF_{p,q} = max\left(\frac{U_p}{U_q}, \frac{U_q}{U_p}\right)$$

- For dataset with multiple groups, GDIF for all groups in dataset:

$$GDIF = \sum_{p,q}^{1 \leq p < q \leq G} GDIF_{p,q}$$

Methodology

GUIDE Framework

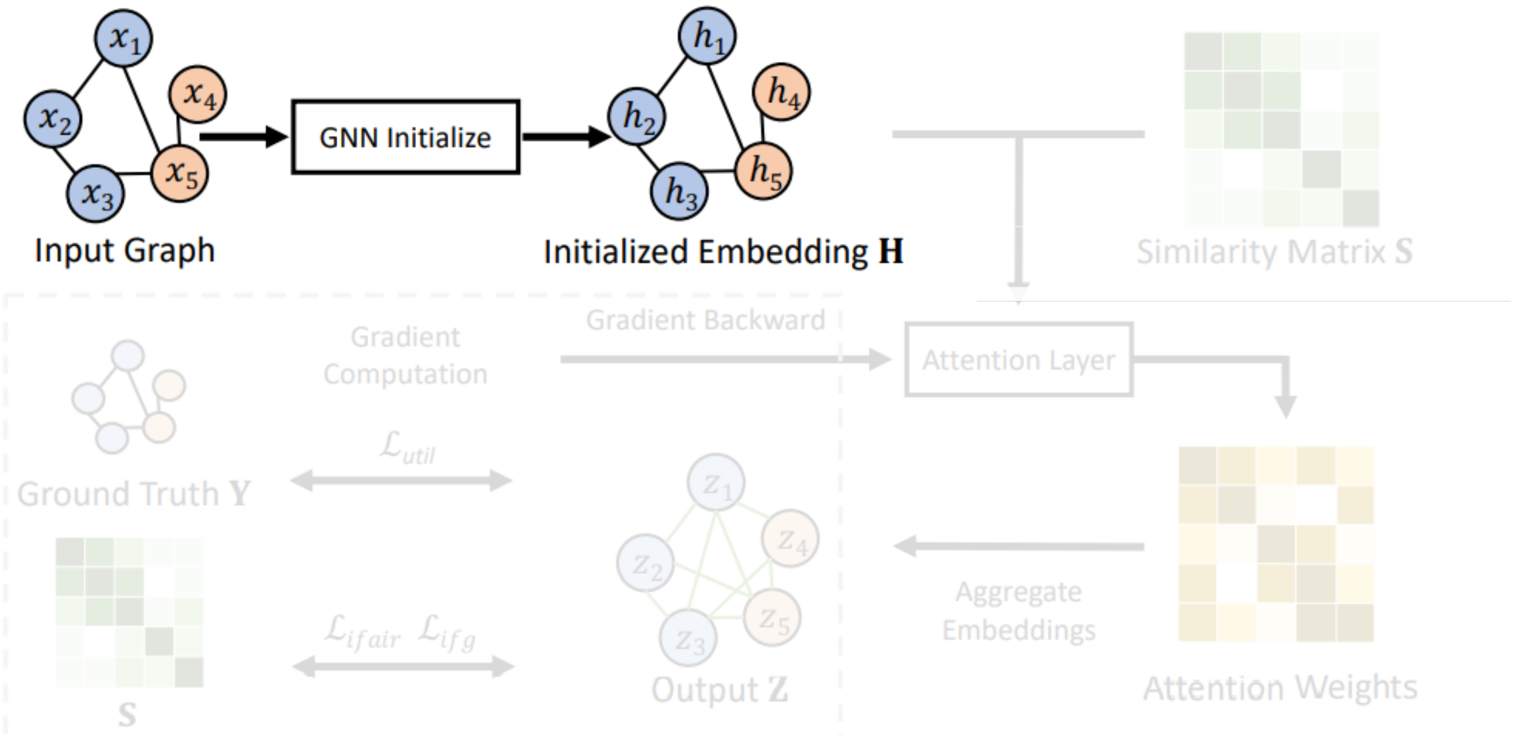


GUIDE includes two main steps:

(1) node embedding initialization and (2) fairness promotion

Methodology

GUIDE Framework



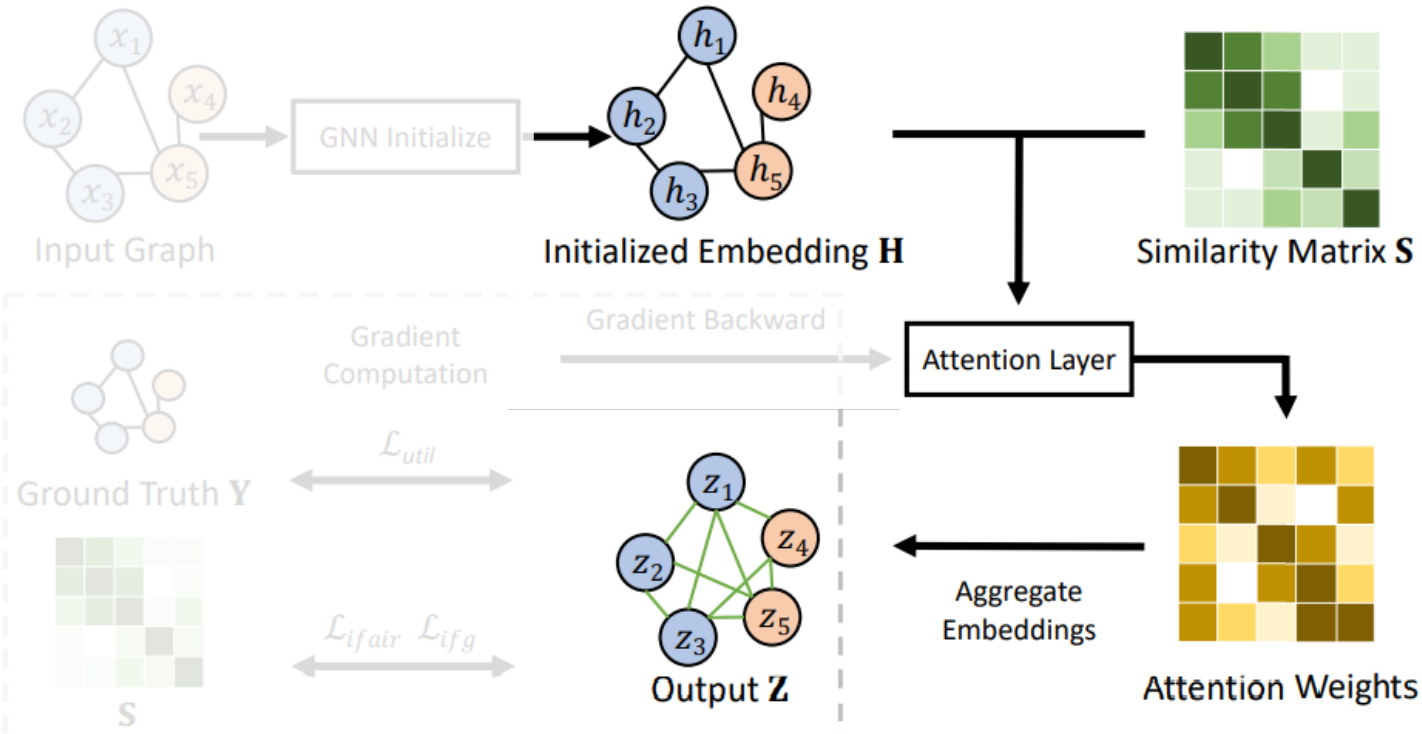
Step 1: Obtain informative embeddings

Embedding initialization with node feature matrix $\mathbf{X}$ and node adjacency matrix $\mathbf{A}$

$$\mathcal{L}_{\text{util}} = -\frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{K} \mathrm{Y}_{ij} \log \hat{\mathrm{Y}}_{ij}$$

Methodology

GUIDE Framework



Step 2: Fairness promotion

Fairness promotion with node similarity matrix **S** and node embeddings **H**

$$\lambda_{i,j} = \frac{\exp(\phi(\mathbf{a}^T[\mathbf{W}\mathbf{h}_i||\mathbf{W}\mathbf{h}_j])\mathrm{S}[i,j])}{\Sigma_{j\in\mathcal{N}_i}\exp(\phi(\mathbf{a}^T[\mathbf{W}\mathbf{h}_i||\mathbf{W}\mathbf{h}_j])\mathrm{S}[i,j])} \qquad \mathbf{z}_i = \sigma(\Sigma_{j\in\mathcal{N}_i}\lambda_{i,j}\mathbf{W}\mathbf{h}_j)$$

Methodology

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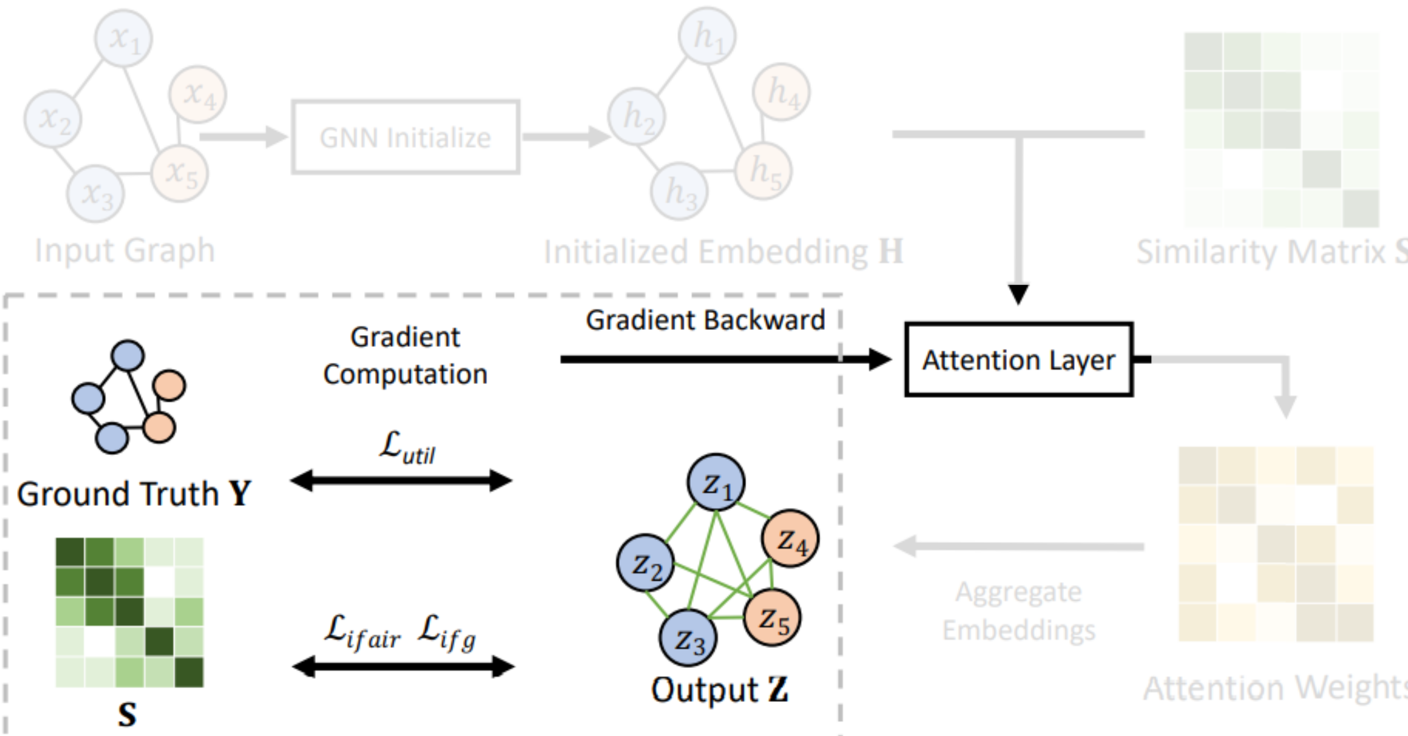


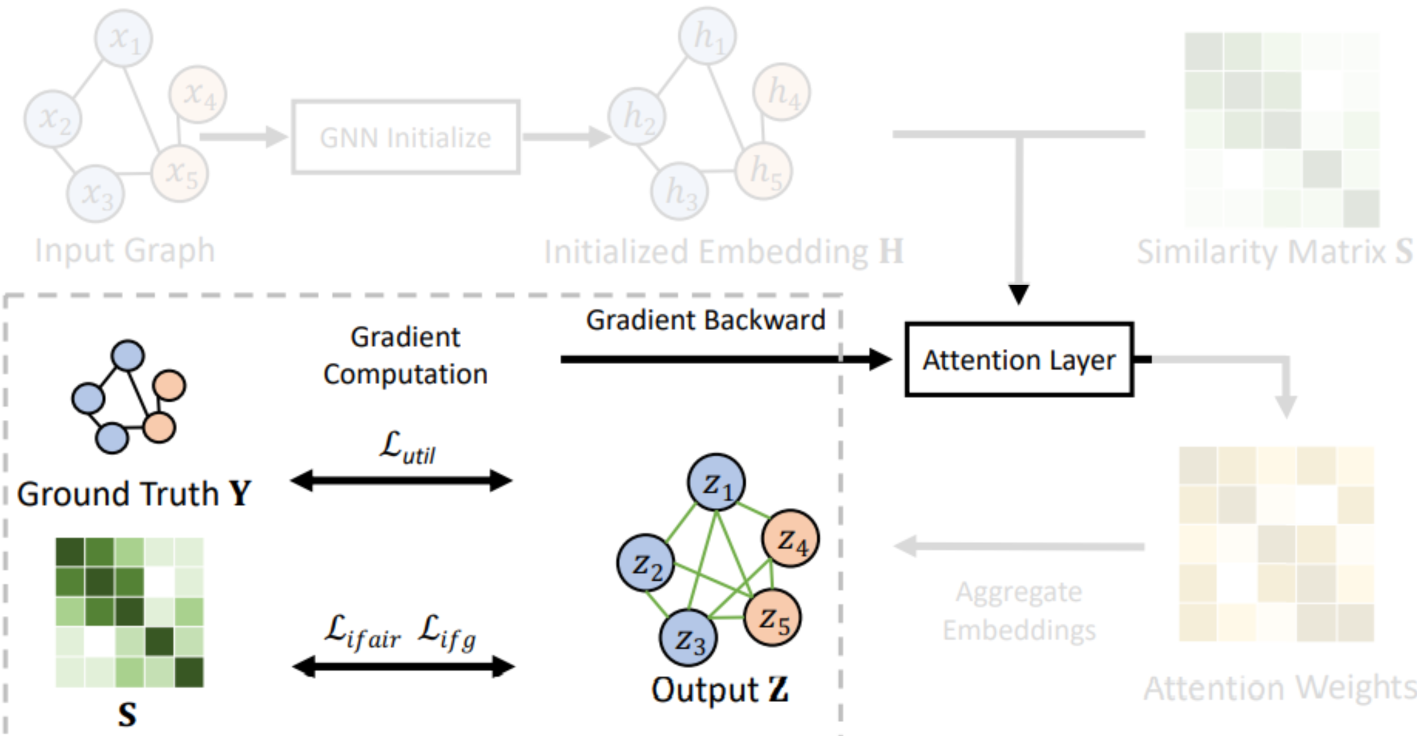
Optimization Objectives

(1) Utility maximization for node classification task

$$\mathcal{L}_{\text{util}} = -\frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{K} \mathrm{Y}_{ij} \log \hat{\mathrm{Y}}_{ij}$$

Methodology

GUIDE Framework



Optimization Objectives

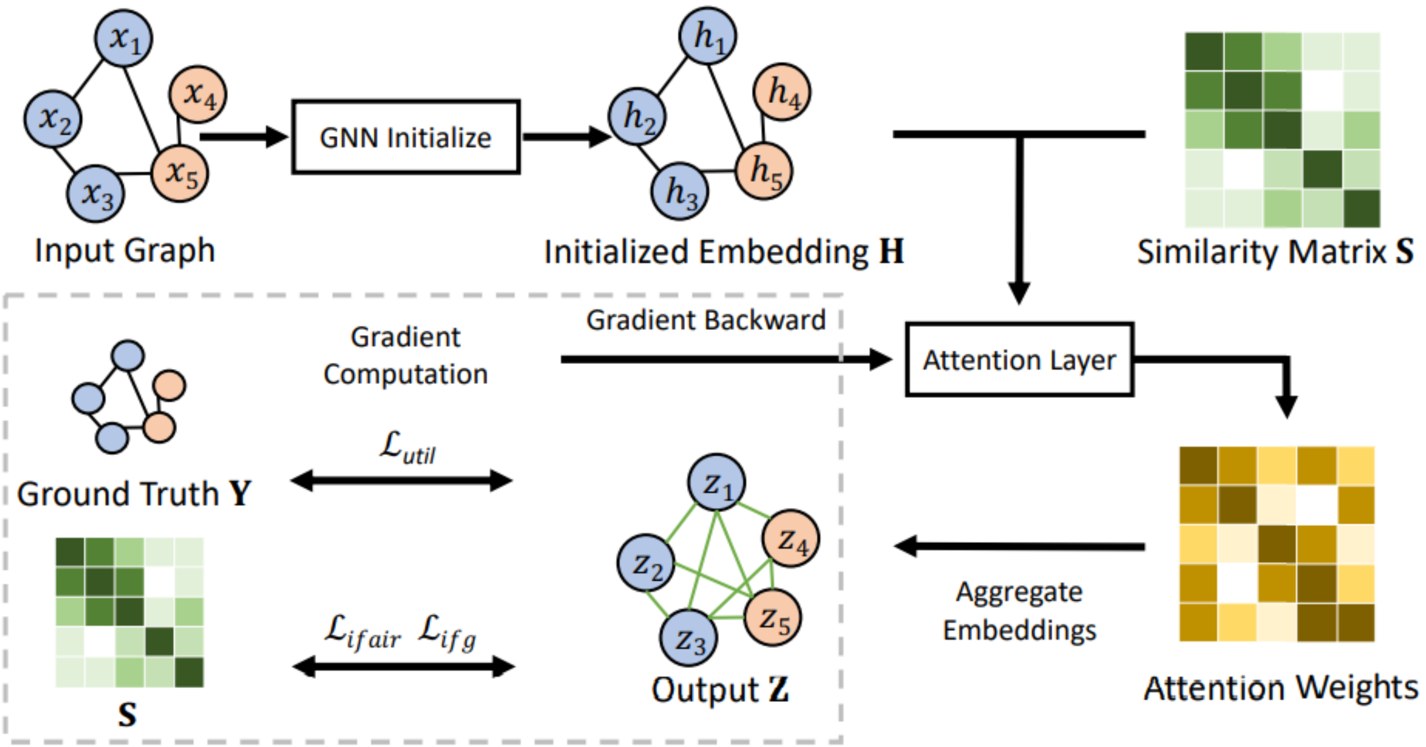
(2) Overall individual (un)fairness minimization and (3) GDIF minimization

$$\mathcal{L}_{\text{ifair}} = \sum_{v_i \in \mathcal{V}} \sum_{v_j \in \mathcal{V}} \|\mathbf{Z}[i,:] - \mathbf{Z}[j,:]\|_2^2 \, \mathbf{S}[i,j]$$

$$\mathcal{L}_{\text{ifg}} = \sum_{p,q}^{1 \le p < q \le G} \left(\frac{U_p}{U_q} - 1\right)^2 + \left(\frac{U_q}{U_p} - 1\right)^2$$

Methodology

GUIDE Framework



Overall Optimization Objectives

(1) Utility maximization, (2) overall individual fairness, (3) group equality of individual fairness

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{util}} + \alpha\mathcal{L}_{\text{ifair}} + \beta\mathcal{L}_{\text{ifg}}$$

Experiments

- **Downstream Task:** Node classification
- **Baselines:** FairGNN [3], NIFTY [4], PFR [5], InFoRM [2]
- **GNN backbones:** GCN [7], GIN [8], JumpingKnowledge [9]
- **Metrics:** AUCROC, Individual (un)fairness, proposed GDIF
- **Datasets:** Credit [10], Income [11], Pokec-n [12]

Dataset	**Credit**	**Income**	**Pokec-n**
# of nodes	30, 000	14, 821	66, 569
# of node attributes	13	14	266
# of edges in A	304, 754	100, 483	1, 100, 663
# of edges in S	1, 687, 444	1, 997, 641	32, 837, 463
Sensitive Attribute	age	race	age

Experiments

Results

Model	AUC(↑)	IF(↓)	GDIF(↓)	AUC(↑)	IF(↓)	GDIF(↓)	AUC(↑)	IF(↓)	GDIF(↓)
Credit									
	GCN			GIN			Jumping Knowledge		
Vanilla	0.68±0.04	39.02±3.78	1.32±0.07	**0.71±0.00**	120.02±15.42	1.75±0.21	0.64±0.11	31.06±13.90	1.32±0.06
FairGNN	0.68±0.01	23.33±12.59	1.33±0.10	0.68±0.02	77.32±48.47	2.18±0.19	0.66±0.02	2.61±1.92	1.52±0.42
NIFTY	**0.69±0.00**	30.80±1.39	1.24±0.02	0.70±0.01	56.43±37.85	1.63±0.27	**0.69±0.00**	26.44±2.39	1.24±0.03
PFR	0.64±0.13	36.58±6.91	1.41±0.08	0.71±0.01	162.58±103.87	2.40±1.23	0.67±0.05	36.30±18.22	1.35±0.03
InFoRM	0.68±0.00	2.41±0.00	1.46±0.00	0.69±0.02	2.94±0.28	1.76±0.17	0.67±0.05	5.66±5.31	1.47±0.16
GUIDE	0.68±0.00	**1.93±0.11**	**1.00±0.00**	0.68±0.00	**2.43±0.02**	**1.00±0.00**	0.68±0.00	**2.34±0.11**	**1.00±0.00**
Pokec-n									
	GCN			GIN			Jumping Knowledge		
Vanilla	**0.77±0.00**	951.72±37.28	6.90±0.12	**0.76±0.01**	4496.47±1535.62	8.35±1.24	**0.79±0.00**	1631.27±93.94	8.47±0.45
FairGNN	0.69±0.03	363.73±78.38	6.21±1.28	0.69±0.01	416.28±402.83	4.84±2.94	0.70±0.00	807.97±281.26	11.68±2.89
NIFTY	0.74±0.00	85.25±10.55	5.06±0.29	**0.76±0.01**	2777.36±346.29	9.28±0.28	0.73±0.01	477.31±165.68	8.20±1.33
PFR	0.53±0.00	98.25±9.44	15.84±0.03	0.60±0.01	628.27±85.89	6.20±0.79	0.68±0.00	729.77±74.62	15.66±5.47
InFoRM	**0.77±0.00**	230.45±6.13	6.62±0.10	0.75±0.01	271.65±30.63	6.83±1.34	0.78±0.01	315.27±25.21	6.80±0.54
GUIDE	0.73±0.02	**55.05±30.87**	**1.11±0.03**	0.74±0.01	**120.65±17.33**	**1.12±0.03**	0.75±0.02	**83.09±18.70**	**1.13±0.02**

Experiments

Results

Model	AUC(↑)	IF(↓)	GDIF(↓)	AUC(↑)	IF(↓)	GDIF(↓)	AUC(↑)	IF(↓)	GDIF(↓)
Credit									
	GCN			GIN			Jumping Knowledge		
Vanilla	0.68±0.04	39.02±3.78	1.32±0.07	**0.71±0.00**	120.02±15.42	1.75±0.21	0.64±0.11	31.06±13.90	1.32±0.06
FairGNN	0.68±0.01	23.33±12.59	1.33±0.10	0.68±0.02	77.32±48.47	2.18±0.19	0.66±0.02	2.61±1.92	1.52±0.42
NIFTY	**0.69±0.00**	30.80±1.39	1.24±0.02	0.70±0.01	56.43±37.85	1.63±0.27	**0.69±0.00**	26.44±2.39	1.24±0.03
PFR	0.64±0.13	36.58±6.91	1.41±0.08	0.71±0.01	162.58±103.87	2.40±1.23	0.67±0.05	36.30±18.22	1.35±0.03
InFoRM	0.68±0.00	2.41±0.00	1.46±0.00	0.69±0.02	2.94±0.28	1.76±0.17	0.67±0.05	5.66±5.31	1.47±0.16
GUIDE	0.68±0.00	**1.93±0.11**	**1.00±0.00**	0.68±0.00	**2.43±0.02**	**1.00±0.00**	0.68±0.00	**2.34±0.11**	**1.00±0.00**
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Observations

- GUIDE achieves the **best fairness performances** across multiple datasets and GNN backbones as shown with the IF and GDIF metrics

Experiments

Results

Model	AUC(↑)	IF(↓)	GDIF(↓)	AUC(↑)	IF(↓)	GDIF(↓)	AUC(↑)	IF(↓)	GDIF(↓)
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Observations

- GUIDE achieves the **best fairness performances** across multiple datasets and GNN backbones as shown with the IF and GDIF metrics
- GUIDE obtains **high fairness optimization** for more expressive GNNs such as GIN

Experiments

Results

Model	AUC(↑)	IF(↓)	GDIF(↓)	AUC(↑)	IF(↓)	GDIF(↓)	AUC(↑)	IF(↓)	GDIF(↓)
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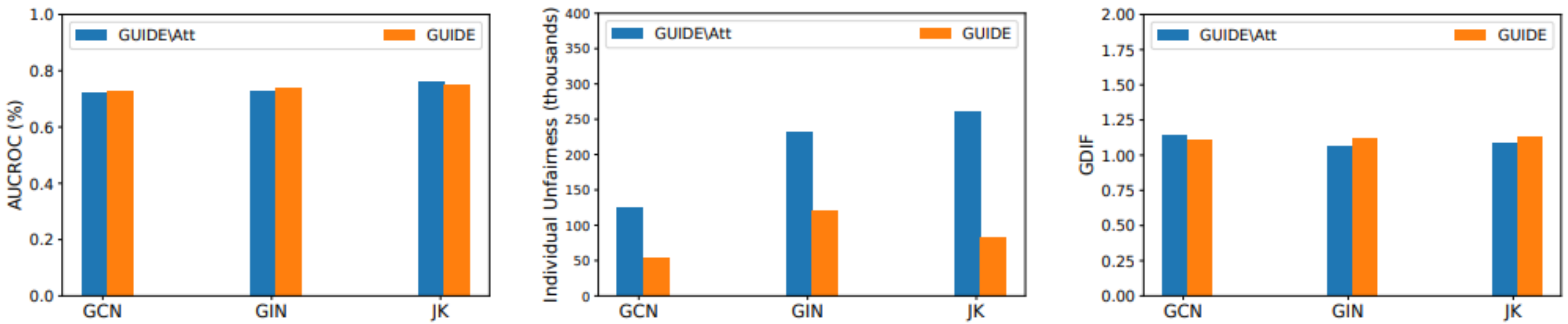
Observations

- GUIDE achieves the **best fairness performances** across multiple datasets and GNN backbones as shown with the IF and GDIF metrics
- GUIDE obtains **high fairness optimization** for more expressive GNNs such as GIN
- GUIDE obtains comparable utility performance in the node classification task compared to baselines

Experiments

Ablation of attention



(a) AUCROC **(b) Individual (Un)fairness** **(c) Group Disparity of Individual Fairness**

Observations

- Backbone GNN without attention mechanism to minimize the same loss function
- Results show **attention help further reduce individual (un)fairness** while having similar AUCROC and GDIF performances

Conclusions

1. Current individual fairness methods **omit group equality constraints** and could cause unfair consequences in critical decision systems
2. GUIDE tackles this issue and **alleviates group disparity of individual fairness in GNNs** while maintaining utility and fairness performances
3. GUIDE is evaluated with extensive experiments to demonstrate its effectiveness in promoting group equality of individual fairness

Acknowledgements

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The End

VIRGINIA DATA SCIENCE AND ANALYTICS (VAST) LAB

Thanks for listening!